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Performance comparison of Image Noise Reduction and Filtering Algorithms

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Abstract: Image noise poses a significant challenge in digital image processing, impacting the quality and reliability of various applications. To address this issue, researchers have developed a multitude of noise removal techniques. In this article, we propose a Modified Wiener filter as a novel approach to combat image noise. Additionally, we explore and compare its performance with other well-known noise removal techniques, including the Adaptive Lee filter, adaptive median filter, and adaptive Wiener filter. By examining the unique characteristics, advantages, and limitations of each method, we aim to provide valuable insights into their effectiveness and applicability in real-world scenarios

Keywords: adaptive Wiener filter, Modified Weiner Filter, Adaptive Lee filter, adaptive median filter

Introduction

As digital images continue to play a vital role in fields such as medical imaging, remote sensing, and computer vision, the demand for robust noise removal techniques becomes increasingly important. To achieve this, researchers have devised advanced noise removal techniques such as the Adaptive Lee filter, adaptive median filter, and adaptive Wiener filter. These methods leverage adaptive algorithms and statistical approaches to estimate local image statistics and optimize noise reduction. Each technique employs adaptive algorithms and statistical approaches to adaptively estimate local image statistics and optimize noise reduction. By understanding the strengths and limitations of these techniques, researchers and practitioners can make informed decisions when selecting an appropriate method for their specific image denoising needs. In this article, we study these filters in addition to a proposed Modified Wiener filter, shedding light on their mechanisms and discussing their performance in various scenarios.

Literature Review

Image processing techniques play a crucial role in enhancing the quality of digital images by removing noise and artifacts. The adaptive median filter is an important method widely employed for noise reduction and preserving edge details. here, we explore relevant studies and developments in the field of adaptive median filtering [1].

The adaptive median filter is an effective technique for noise removal, particularly in images with varying levels of noise and complex backgrounds. In their seminal work, P. K. Sahoo, S. Soltani, and K. C. Wong (1988) proposed the concept of the adaptive median filter, which analyzes the local neighborhood of pixels and adjusts the filter window size accordingly to adapt to different noise levels. Their method demonstrated superior noise reduction performance compared to traditional fixed-size median filters. Since the introduction of the adaptive median filter, several extensions and improvements have been proposed to enhance its capabilities. K. G. Cortelazzo and M. L. Trivedi (1994) introduced a modified adaptive median filter that incorporates spatial information to achieve better noise suppression in textured and non-textured regions. S. S. Again et al. (2007) presented an improved adaptive median filter that utilizes morphological operations to enhance the filtering process and handle impulse noise effectively. The adaptive median filter finds extensive applications in medical imaging, where preserving fine details and reducing noise are crucial for accurate diagnosis. In their study, R. Raju et al. (2014) applied the adaptive median filter to denoise magnetic resonance images, leading to improved image quality and more reliable analysis. Y. Wang, H. Yu, and Y. He (2020) proposed an adaptive median filtering approach for ultrasound image enhancement, enhancing the visibility of structures and improving diagnostic accuracy.

Materials and Methods:

1- Adaptive Lee Filter (ALF)

The Adaptive Lee filter is a widely used technique in image processing for speckle noise reduction in remote sensing and ultrasound imaging. This section provides an overview of the Adaptive Lee filter, its applications, and key studies in this field.

The Adaptive Lee filter is a statistical filtering technique that effectively suppresses speckle noise while preserving image details. It adaptively estimates the local statistics of the image, adjusting the filter parameters to achieve optimal noise reduction results. This filter is particularly useful in applications where preserving image features and maintaining fine details are crucial.

Lee introduced the concept of the sigma filter, which is the foundation of the Adaptive Lee filter. The sigma filter estimates local statistics to adaptively adjust the filter parameters, providing effective speckle noise reduction [8].

Wu, Huang, and Liao proposed a new adaptive filter based on the Lee filter for speckle noise reduction in ultrasound images. The filter adaptively estimates the local statistics and incorporates a novel weight function to enhance noise reduction performance [14].

Bae and Kang developed an adaptive Lee filter specifically for polarimetric synthetic aperture radar (SAR) data. The filter adaptively estimates the covariance matrix to effectively reduce speckle noise in SAR images, improving image quality and interpretation [2].

Qu, Huang, and Xu proposed an adaptive polarimetric Lee filter for speckle noise reduction in polarimetric SAR images. The filter adaptively estimates the covariance matrix of polarimetric data to achieve optimal noise reduction while preserving polarimetric information [11].

These studies by Lee, Wu et al., Bae and Kang, and Qu et al. have contributed significantly to the development and application of the Adaptive Lee filter in different domains. These studies showcase the effectiveness of the Adaptive Lee filter in enhancing image quality while suppressing speckle noise.

The Lee filter (LF) stands as an adaptive filter for noise diminution that conserves the edges of the image for effective used. The mathematical illustration for LF denoising is formulated as given in equ (1).

$$H = \overline{m} + W \times \left(C - \overline{m}\right) \qquad (1)$$

Where, represents a denoised image, indicates mean intensity of the filter window, implies the weight function and is a central element in the filter window[6].

By applying the ALF, each pixel on an image is considered and supplanted by the center value of its surrounding pixels. Initially, the center value is estimated by sorting the whole pixel values as of the filter window in to numerical order[6]. On the off-chance that the neighborhood pixels consist of an even number of pixels, the pixel values' average is utilized as the center value. Then the old center pixel value in filter window is swapped with the newly sorted pixel value. This helps to replace the noisy pixels on an image. To ameliorate the performance in edge areas, a refinement is done to the original LF, wherein the neighborhood used in high variance areas for the calculation of the local statistics took on board the orientation of a possible edge. Therefore, the weighting function of LF is written as given in eq. (2).

$$W = \frac{\sigma^2}{\sigma^2 + \rho^2} \qquad (2)$$

Here, denotes a weighting function, indicates variance of the image, in which represents the variance of pixels in filter window.

Adaptive Median Filter(AMF)

The adaptive median filter is a widely used technique in image processing for noise reduction and preserving image details. This section review aims to provide an overview of the adaptive median filter, its applications, and key studies in this field.

Adaptive Median Filter is a nonlinear filtering technique that adjusts the filter size based on the local characteristics of the image. It is effective in removing different types of noise, including salt-and-pepper noise and impulse noise, while preserving important image details. The filter adaptively analyzes the pixel neighborhood and applies a variable-sized window to obtain better noise reduction results.

Lee proposed the adaptive median filter for impulsive noise removal in highly corrupted images. The filter adjusts the window size based on the local noise characteristics, achieving effective noise reduction[7].

Huang and Russell introduced new algorithms for adaptive median filters, improving their noise removal capabilities. The study presented various techniques for selecting the window size, enhancing the adaptivity of the filter[4].

Bhargava and Shah proposed an adaptive impulse noise removal method using progressive switching median filters. The technique effectively detects and removes impulse noise while preserving image details[3].

Zhang and Wang introduced an adaptive fuzzy switching weighted median filter for salt-and-pepper noise removal. The filter adapts the weights based on the local image characteristics, resulting in improved noise reduction performance[15].

The adaptive median filter is a powerful tool for noise reduction in image processing. Through adaptive window sizing and analysis of local image characteristics, it effectively removes noise while preserving important image details. Previous studies by Lee, Huang and Russell, Bhargava and Shah, and Zhang and Wang have made significant contributions to the development and improvement of adaptive median filters.

In AMF procedure, the size of filter window is modified in accordance to the noise density. Median filters changes the SPN values and retains the grey values of the image as it is. In the process of detecting the noise points, pixels are just divided into two categories based on Pmax and Pmin, thereby making it easy to sort image of pixels into noise points. To prevent sorting Pmax into noise point, a variable (LS) least set difference is introduced and Ω represents the set of non pollutant points.

$$LS = \min\{|P_{ij} - P_{zk}|\} \quad (3)$$

Where Zk is pixel values in neighborhood of non pollutant points.

The first step computes the value of Pmin and Pmax by sorting the gray values of pixels in the working window Wij . The minimum pixel value is assigned Pmin and the maximum value is assigned Pmax . The average intensity values of the pixels is assigned Pmed. The next step checks if Pij is a pulse or noise point. If it is a pulse it is then added to the set of non pollutant set. If the size of the window is less than maximum window size, the width of the working window is increased by two. If it is greater than the maximum window size, Pij remains unchanged (if Ω is empty) otherwise LS is computed and the filter output is Pij (If LS ≤ Threshold) else Pij becomes a noise point and the output is Pmed (median value of Ω). Figure (1) illustrates the AMF procedure.

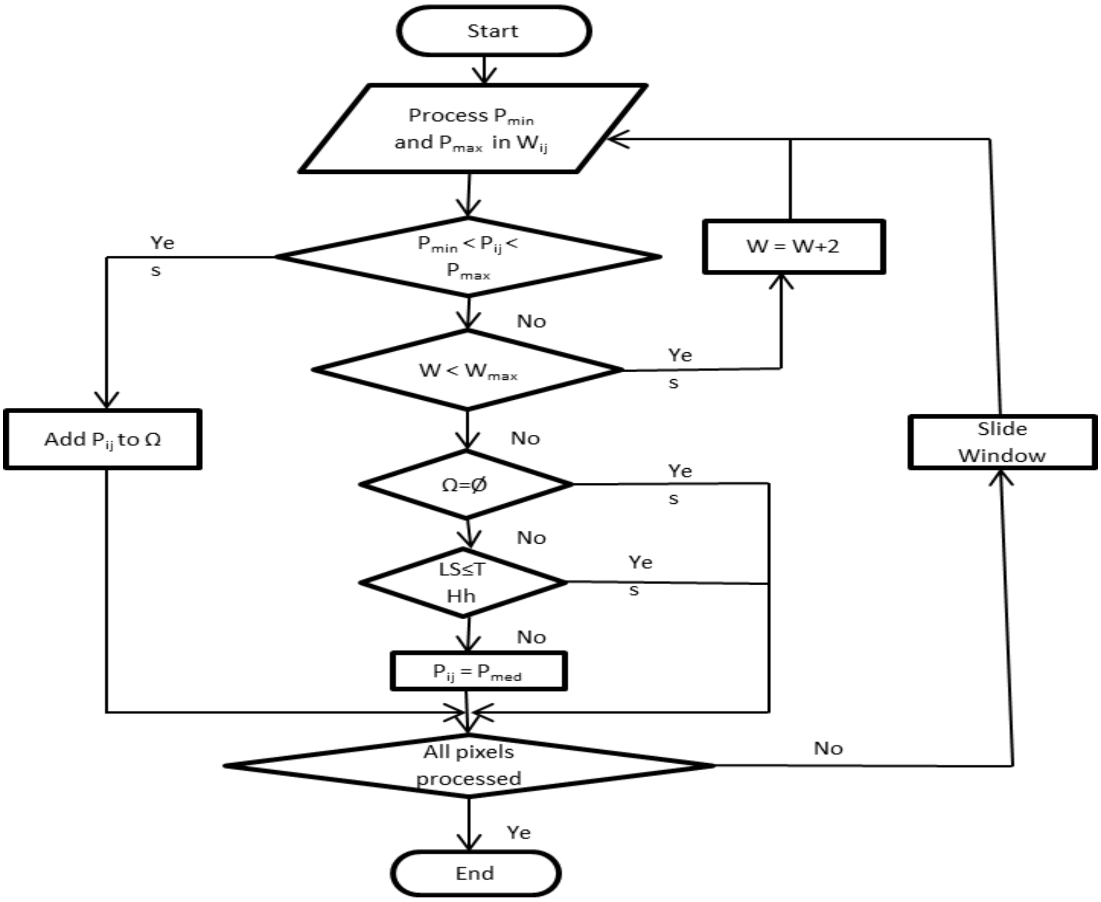

Figure (1) illustrates the AMF procedure

Utilizing this algorithm the SPN is removed and the noise-free I'_f image is obtained.

Let Pij be the pixel value of point (i,j) of the original image If (N), Wij be the present working window. Let Pmin, Pmed, Pmax be the minimum, intermediate and maximum pixel value respectively. Suppose maximum window is Wmax , LS of threshold, Th, with window set to Wij, Width W=3 and Ω = Ø.

Step 1: Compute the values of Pmin and Pmax with Wij for current pixel.

Step 2: If Pmin < Pij < Pmax

Then Pij remains unchanged and Add the non pollution point from Wij into Ω

Step 3: If W < Wmax

Set W= W +2 (increment width by 2)

Step 4: If W ≥ Wmax

Check if Ω = Ø

Pij remains unchanged

Otherwise Compute LS of Pij by eq (3)

If LS ≤ Th

Filter output is Pij

Else

Pij is the noise point and filter output is Pmed (median value of set Ω)

Proceed to Sep 5

Step 5: The procedure is recursed until all pixels are processed.

Utilizing this algorithm the SPN is removed and the noise-free I'_f image is obtained.

2- Existing Adaptive Wiener Filtering(AWF)

The inverse filtering is a restoration technique for deconvolution, i.e., when the image is blurred by a known lowpass filter, it is possible to recover the image by inverse filtering or generalized inverse filtering[10]. However, inverse filtering is very sensitive to additive noise. The approach of reducing one degradation at a time allows for the development of a restoration algorithm for each type of degradation and simply combine them. The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. The Wiener filter removes the additive noise and inverts the blurring simultaneously. The Wiener filter is based on a statistical approach. The WF stands as a linear estimation of the original image [9]. The block diagram of wiener filter is given in figure(2).

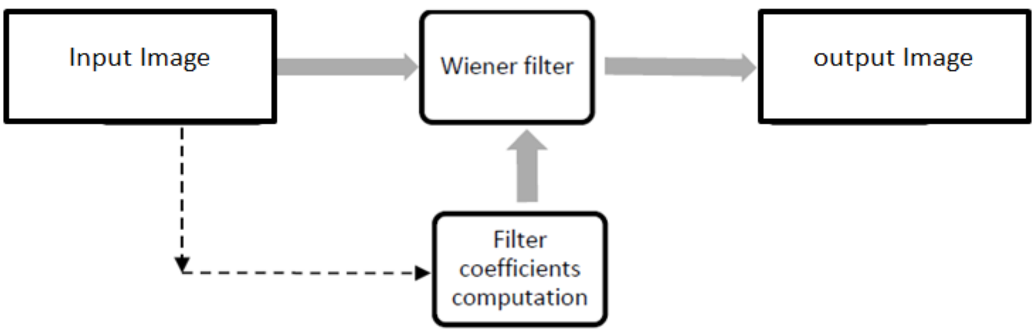

Figure 1: Block diagram of the Wiener Filter

The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing [5]. Wiener filters are usually applied in the frequency domain. Given a degraded image x(n,m), one takes the Discrete Fourier Transform (DFT) to obtain X(u,v). The original image spectrum is estimated by taking the product of X(u,v) with the Wiener filter G(u,v):

$$\hat{s}(u,v) = G(u,v)X(u,v) \qquad (4)$$

The inverse DFT is then used to obtain the image estimate from its spectrum. The Wiener filter is defined in terms of these spectra:

$H(u,v)$ Fourier transform of the point-spread function (PSF).

$P_\theta(u,v)$Power spectrum of the image process, obtained by taking the Fourier transform of the image autocorrelation.

$P_\Omega(u,v)$Power spectrum of the noise process, obtained by taking the Fourier transform of the noise autocorrelation.

The Wiener filter is expressed below

$$G(u,v) = \frac{H(u,v) * P_\theta(u,v)}{H(u,v)^2 P_\theta(u,v) + P_\Omega(u,v)} \qquad (5)$$

For the case of additive white noise and no blurring, the wiener filter simplifies to:

$$G(u,v) = \frac{P_\theta(u,v)}{P_\theta(u,v) + \sigma_\Omega^2} \qquad (6)$$

Where σ_Ω^2 is the noise variance.

Also Proposed a technique for removal of speckle noise from images using a combination of hybrid wiener-median filter[12].

Initially logarithmic transform of the noisy image was computed. This step is performed because speckle noise is a multiplicative noise.

The Mean-squared Methods uses the fact that the Wiener Filter is one that is based on the least-squared principle, i.e.the filter minimizes the error between the actual output and the desired output. To do this, first the variance of the data matrix is to be found. Then, a box of certain size is passed around the matrix, moving one pixel at a time[13]. For every box, the local mean and variance is found. And the filtered value of each pixel is found by the following formula:

Weiner Filter estimates the local mean and variance around each pixel

$$M' = \frac{1}{NM} \sum_{i,j \in \eta} G(i,j) \qquad (7)$$

$$\sigma^2 = \frac{1}{NM} \sum_{i,j \in \eta} G^2(i,j) - M'^2 \qquad (8)$$

Where η is the $N - by - M$ Local neighborhood of each pixel in the image G, this creates a pixel-wise Wiener Filter using these estimates.

Weiner Filter based on mean squared method is expressed by using the equation:

$$b(i,j) = M' + \frac{\sigma^2 - r^2}{\sigma^2}\left(G(i,j) - M'\right) \qquad (9)$$

Where, $b(i, j)$ represent the MWF in the time domain, $M^{'}$ is the local mean around each pixel, σ^2 denotes the variance and also r^2 represents the noise variance. The frequency domain (FD) representation of the image G_i is $G(u, v)$.

3- Proposed Modified Wiener Filter(MWF)

Weiner filter (WF) is effectual in the existence of random noise like the Gaussian noise. The inverse filtering stands as a restoration method for deconvolution, explicitly when the image is blurred via a known low pass filter; it is probable for recovering the image by means of inverse filtering or else generalized inverse filtering. Nevertheless, inverse filtering is exceptionally responsive to additive noise. It eradicates the additive noise and also inverts the blurring concurrently. The general Weiner filter produces results that are often too blurred and spatially invariant. A modified Wiener Filter (MWF) was proposed to overcome this problem.

The gray scale image G_i is imposed as the input to the MWF. Here the quantity of noise that exists in the image was minimized. This was performed by comparing the received image with an assessment of a preferred noiseless signal. This involves the diminishment of the median square error.

The original wiener filter uses the mean value ($M^{'}$) for the filtering process. In this approach , the filter continuously looks at its nearby neighbours to decide whether or not it is a representative of its surroundings, if it is not that pixel value is replaced with the mean of its neighbouring pixel values. This approach leads to a wide discrepancy in some pixel values thus affecting the image preservation details. A different approach was utilized for computing $M^{'}$ in our proposed wiener filter. The median was utilized. This approach preserves the image details better. Instead of just replacing pixel values with mean of their neighbourhood, we utilized the median and M' is derived as follows:

Sort all the pixels in ascending order , if a pixel is not a representative of its neighbourhood. The neighbourhood is sorted in ascending order and the pixel value is simply replaced by the median value of its neighbourhood. This will allow the noisy pixel to take a value that is closer to its neighbourhood pixels thus preserving the image details.

The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.) Figure illustrates an example calculation.

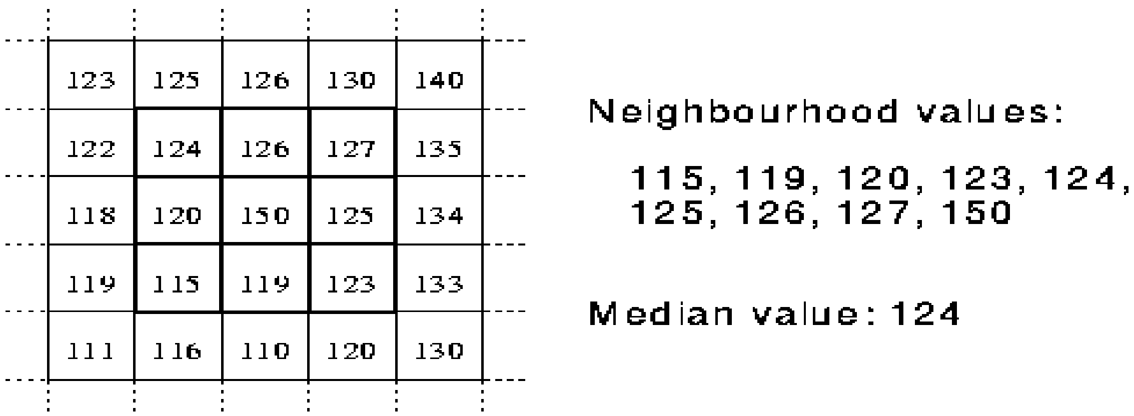

Figure 2: An example of pixel median computation

From the above formula (9), it can be seen that if the original pixel value is similar to the local variance then the filtered value will be that of the local median, if the original pixel value is very much different from the local median, then it will be filtered to give a higher/lower intensity pixel depending on the differences. Also, if the local variance is similar to the matrix variance, which is around 1 (i.e. only noise exists in the box) then the filtered pixel will be that of the local median, which should be close to zero.

The filter is a slight modification of equation (10). In this approach we compute median and also the added with the noise variance to get the smoothed image.

The filtered image is mathematically written as shown below.

$$W(u,v) = M' + \frac{\sigma^2 + r^2}{\sigma^2}\left(G(i,j) - M'\right) \quad (10)$$

Where, represent the MWF for filtered value of each pixel, is the local median around each pixel, denotes the variance and also represents the noise variance. The G(i,j) represent the 'gray scale image' on the time domain.

$$P(u,v) = W(u,v).G(u,v) \quad (11)$$

Where, is the 'filtered image' on the FD, is the 'modified wiener filter' on the FD and is the 'gray scale image' on the FD. Figure (3) Shows the block diagram of the proposed wiener filter.

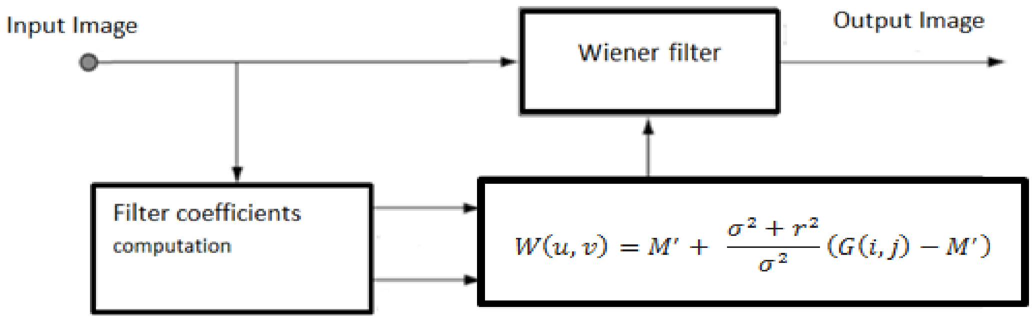

Figure 3 : Block diagram of Modified Wiener Filter (MWF)

Results and Discussions

This paper focuses on the evaluation and comparison of various image filters, including the Modified Wiener Filter, Wiener Filter, Median Filter, and Adaptive Lee Filter. These filters are widely used in image processing applications for noise reduction and image enhancement.

The Modified Wiener Filter is a variant of the traditional Wiener Filter that incorporates additional modifications to improve its performance in noisy environments. It utilizes statistical properties of the image and noise to achieve optimal noise reduction results.

The Wiener Filter is a classical linear filter used for image denoising. It assumes a stationary signal and stationary noise in the frequency domain, and it aims to minimize the mean square error between the filtered image and the original image.

The Median Filter is a non-linear filter that replaces each pixel value with the median value of its neighborhood. It is effective in removing impulse noise and preserving edges, but it may result in blurring of fine details.

The Adaptive Lee Filter is a statistical filter that adapts to local image characteristics and effectively reduces speckle noise while preserving important image details. It estimates local statistics and adjusts filter parameters for optimal noise reduction.

This section of the paper compares and evaluates the performance of the proposed modified wiener filter in terms of PSNR. The proposed filters performance is contrasted with other existing filters say wiener filter, median filter and averaging filter.

The preprocessing uses the MWF to abolish noise. The PSNR ('Peak Signal to Noise Ratio') that is associated with the application of each filter is estimated for database. These values are contrasted with the existing filters like the Wiener Filter, Median Filter , Lee Filter and MWF,. The PSNR determines the image quality.

The higher PSNR value denotes high quality.

Table 1: PSNR values for the proposed MWF filter and the other existing filters that are implemented using database .

Frames	PSNR Values			
	MWF	ALF	AWF	AMF
1	46.0367	38.18555	37.66491	36.78769
2	46.034	38.06246	37.66592	36.78691
3	46.0699	38.08859	37.67718	36.81163
4	46.09185	38.13165	37.67269	36.77833
5	46.08754	38.00522	37.68014	36.75052
6	46.06611	38.03343	37.66249	36.76345
7	46.04962	38.09444	37.63714	36.74512
8	46.0495	38.99484	37.62195	36.7016
9	46.052	38.12629	37.61009	36.71103
10	46.04714	38.13046	37.60655	36.7027

Figure (4) below displays that the value of PSNR for database is the highest for the filter that is used in the proposed technique that is the MWF. The Wiener filter produces results that are slightly under the MWF.

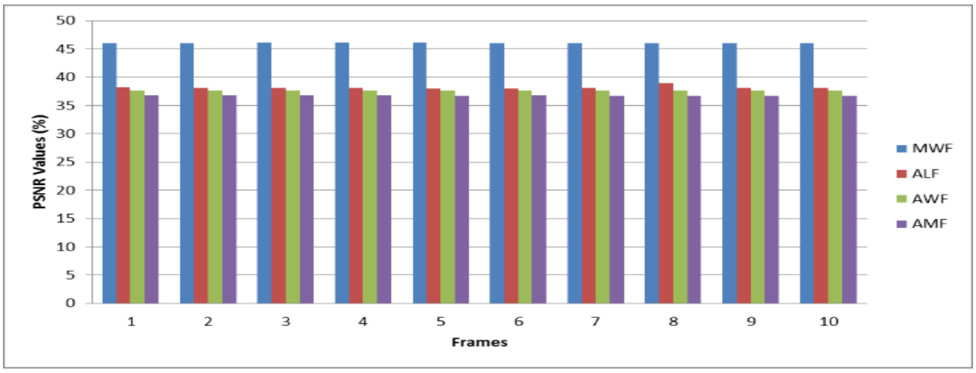

Figure 4: Performance evaluation of MWF on database

Figure 4 above shows the PSNR values of the proposed and existing techniques. The proposed MWF has the highest PSNR value of 46.09185 at fourth frame, while AMF has the lowest PSNR value of 36.7016 at eighth frame. AWF has the highest PSNR value of 37.60655at tenth frame.

Conclusion

In conclusion, the research paper comprehensively evaluated and compared the performance of four image filters: the Modified Wiener Filter, Wiener Filter, Median Filter, and Adaptive Lee Filter. The findings of this study contribute to the understanding of these filters and their suitability for various image processing applications.

The Adaptive Lee filter is a statistical filtering technique that effectively reduces speckle noise while preserving important image features. It adaptively estimates local statistics and adjusts filter parameters to achieve optimal noise reduction results. On the other hand, the adaptive median filter addresses impulse noise by replacing pixel values with the median of neighboring pixels, effectively smoothing out noise while preserving edges. The adaptive Wiener filter utilizes the statistical properties of the signal and noise to remove noise from images, assuming a stationary signal and stationary noise. Lastly, our proposed modified Wiener filter introduces modifications to enhance its performance in noisy environments. This filter combines the principles of the Wiener filter with additional enhancements to achieve improved noise reduction and image quality. Moreover, the PSNR values that were attained by the employment of the MWF were much above the values that were obtained using other filters.

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